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DETECTION OF ABNORMAL BEHAVIORS IN CROWD SCENE: A REVIEW

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Abstract

Crowd analysis becomes the most active-oriented research and trendy topic in computer vision nowadays. Typically, crowd is a unique group of individual or something involves community or society where the phenomena of the crowd are very familiar in a variety of research discipline such as sociology, civil and physics [1]. Within the crowd, there exist many behavior anomalies or abnormality. There are many ways of detecting these abnormalities such as crowd density estimation, crowd motion detection, crowd tracking and crowd behavior recognition. All of these protocols normally involve three steps: pre-processing, object detection and event/behavior recognition. In this paper, we provide state-of-the-art of crowd analysis from 2000 until now. Based on our analysis from these substantial reviews, we propose a general framework and pattern taxonomy of detecting abnormal behavior in a crowded environment accordingly.

Keywords: *Video Surveillance, Crowd Scene, Crowd Analysis, Abnormal behavior.*

1 Introduction

The issue such as complexity and abstract of identifying and detecting abnormal behavior in crowd scene attract many researchers [2]. Handling the situation that relate with the abnormal in a crowd is not easy [3]. The most important issue in this scenario includes the density of the crowded scene and the state of being normal or abnormal. Nonetheless, there are some difficulties in analyzing human behavior in crowd scene, and the most common approach is conducted by using video surveillance [4-6].

With the intelligent digital camera technology, i.e., Closed-Circuit Television (CCTV), video surveillance is becoming apparent in this field to observe some parts of a process from control environment which is required in every intelligent crowd scene. One of such topics in video surveillance is about crowd analysis. Video surveillance application uses crowd analysis for automatic detection of anomalies and alarms [6]. Crowd analysis consists of four components and these include crowd density estimation, crowd motion detection, crowd tracking and crowd behavior understanding [2, 4, 5, 7]. Typically in a crowd analysis, the application involves crowd management strategies, public space design, virtual environments, visual surveillance and intelligent environment [6]. However, in this paper, we are focusing on the visual surveillance crowd analysis application.

During last decade, research on detecting abnormal behavior has actively evolved taking the advantage of recent developments in some related fields such as Computer Vision (CV), Pattern Recognition (PR), Soft Computing (PR), Mathematical Modeling (MM), Biomedical Information (BI), Image Signal Processing (ISP), Data Mining (DM), Computational Intelligent (CI) and Artificial Intelligence (AI). In this paper, a review of the recent advances in the area of detecting abnormal behavior for human in crowded scene is presented since 2000; unless that are some material facts that is necessary to state a research prior than that.

The remainder of the paper is organized as follows: Section II presents the general concept of video surveillance in crowd scene and description of the crowd analysis involving the processing steps for analyzing the crowd behavior. Section III reviewing some previous works related to the detection of abnormal behaviors. Section IV presents a new taxonomy of abnormal behavior in crowd scene, follows by a conclusion of this study.

2 Video Surveillance – An Overview

Video surveillance application has been around since 1950's. In the recent studies, a wide variety of application domain have been applied especially in crowded and security-sensitive spot such as railway station, public squares, military and underground walkways [8, 9]. The important element of video surveillance is not only on the placement of the cameras for human eyes, but also for fully automated surveillance activities [9]. Although object recognition and shape estimation problems have been solved by previous studies in a past few years, but with the exponential growth of advanced video surveillance devices and technology, a lot of tasks can be improved in terms of the accuracy and the reliability of target detection, tracking, classification and behavior analysis [10, 11].

Recently, video surveillance is used to evaluate image sequence that effectively reduces the problem of detecting moving object. The problem of inability and reliability to measure size and position of the 3D object in a scene is also considered [12] which include many complexity factors that could affect the detection such as weather, lighting, types of object motion and etc. So, the procedural type design of video surveillance need to be generalized and categorized to get the require information[13]. The privacy issues and the tool performance of the video surveillance has completely addressing in [10]. Various functionality of video surveillance has also been determined, and these include detection algorithm, tracking target in the field, classification specific domain and analyzing performance (for example size, color and speed) for detecting problem in crowd area [10]. Further study on the current state of art in development of video surveillance is describe in [14] which provides the history and evolution of video surveillance system from the first generation up to the third generation.

Video surveillance framework is presented by researchers, where the aim is to describe the object or human behavior of each scene. For example, In the year of 2004, Weiming et al [9] summarized the detailed task with discussing a different method based on merit and demerits especially for motion detection and tracking. Various issues are examined by them and dividing categories of sub process based on the state of art. In order to overcome the problem, general framework of video surveillance is illustrated to review the prerequisite stage of processing. The effective stage involve modeling of environments, detection of motion, classification of moving object, tracking, understanding and description of behavior and human identification. Figure 1 shows the general framework of video surveillance proposed by Weiming et al. Meanwhile Table 1 describes the term of each aspect of proposed framework.

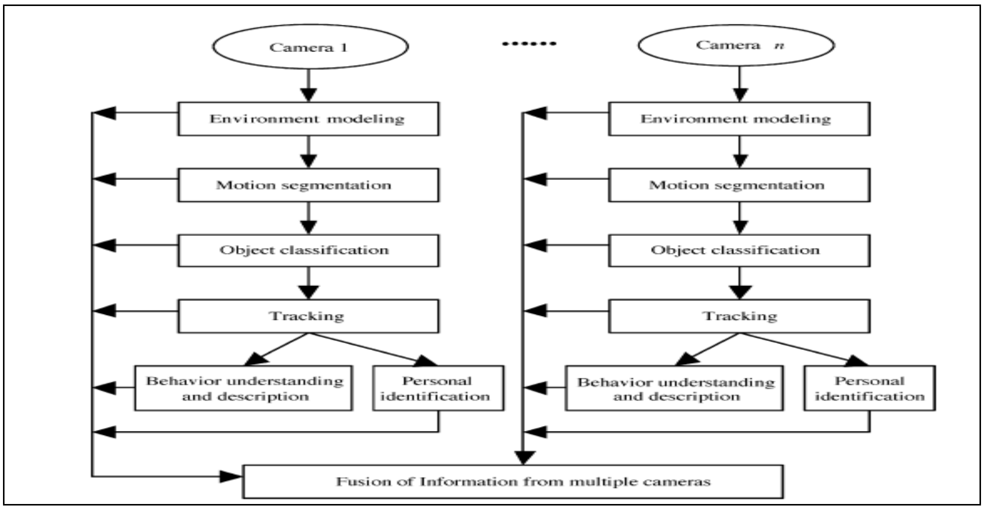

Figure 1: General framework for video surveillance proposed by Weiming et al[9]

Table 1 : Description of subsequent process[9]

Process	Task	Feature/approach
Environmental Modeling	Construct and updating background images from dynamic sequence	2-D models and 3D models
Motion segmentation	Detect regions corresponding to moving object	Background subtraction, Temporal differencing, optical flow
Object classification	Different moving regions correspond to different moving target scene	Shape-based classification, motion based classification
Object tracking	Track moving objects from one frame to another in image sequence	Region-based tracking, Active Contour-based tracking, feature based tracking, model based tracking
Understanding and description of behavior	To learn the reference behavior sequence from training sample.	- Understand behavior : Dynamic time warping (DTW), Finite State Machine (FSM), Hidden Markov Model (HMM), Time-delay neural network (TDNN), syntactic technique, self-organizing neural network -Natural language description of behavior: Statistical Model and Formalized reasoning
Personal identification	To treat a special behavior understanding problem	Model Based Methods, Statistical methods, Physical –Parameter Based methods, Spatio-Temporal Motion Based Methods, Fusion of Gait with other Biometrics
Fusion of data from multiple cameras	View information that can overcome occlusion	-

Deviation of abnormal behavior from normality model is one of the most challenging problems in video surveillance [15]. And because of that, Antonakaki et al presents a bottom up approach of video surveillance to classify and understand the human behavior (normal or abnormal) using different criteria. In their research, two classification criteria are applied consist of short term behavior and trajectory. Therefore, to make this problem tractable, they setup the precise model framework for video surveillance system. This framework is quite similar with the previous framework that proposed by Weiming et al in 2004. But in Antonakaki et al, they try to advance the framework by dividing the level of framework into two layers: Low level (motion detection, object classification and object tracking) and High level (motion analysis, behavior understanding, and behavior description). Figure 2 presents the framework proposed by Antonakaki et al and table 2 will describes for each aspects in a video surveillance.

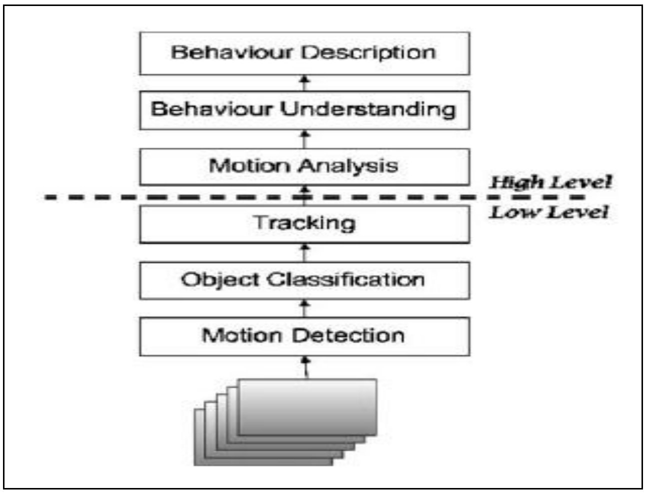

Figure 2: The framework for video surveillance systems by Antonakaki [15].

Table 2: Description of the video surveillance aspects [15]

Term	Definition	
Motion detection	• Focused static or adaptive background subtraction or temporal differencing algorithms. • To separate the foreground pixels that participate into any kind of motion observed in a given scene.	LOW LEVEL
Object classification	• Classify detected objects into such classes as humans or vehicles that appear in a given scene.	
Object detection	• Locate the time and extract trajectories.	
Motion analysis	• Use motion information from low level to identify the types of moving object.	HIGH LEVEL
Behavior understanding	• Classify the activities (walking, running, fighting) and calculate features of motion itself. • Perform recognition of behaviors based on these features values.	
Behavior description	• Classify into a primitive actions. • Recognize behavior through a nearest-neighbor classification.	

Could you imagine possibility a thousand of hours in duration are given in a long time video while you are asked to analyze the video to find an abnormal behavior in a crowd? In video surveillance application, abnormal behaviors are those that should reported for further examinations? What is actually made the abnormal behavior in crowd scene is hard to detect? The reason from all the question maybe abnormal behavior in crowd are rare, difficult to describe, hard to predict and can be subtle [16]. So, based on the proposed framework present at figure 1 and figure 2, we can summarize that the entire framework shows the important image processing in video surveillance. That's why, for the task that include detecting and understanding behavior especially in a crowd scene, video surveillance is the best choice at all. To get more clearly about this, we prepared some basic analysis about crowd in the next section.

2.2 Crowd Analysis

Crowd analysis becomes the most active-oriented research and trendy topic in computer vision nowadays. The potential of crowd behavior analysis lend itself to a new application domain such as automatic detection of riots or chaotic acts in crowds and localization of the abnormal regions in scenes for high resolution [17, 18]. The establishment of model behavior for describing individual and group behaviors in crowded scene already discuss in [19-21]. Variant subtopic for detecting behavior will be find related to the crowd analysis such as crowd density estimation, crowd tracking, crowd behavior, crowd detection (Figure 3).

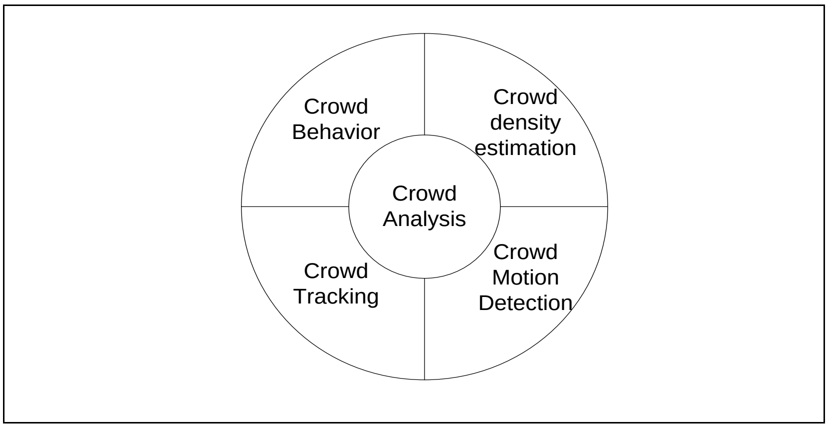

Figure 3: Crowd Analysis

Crowd is a unique group of individual or something involves community or society where phenomena of the crowd are very familiar in a variety of research discipline such as sociology, civil and physics [1]. Crowd can be described in a general term, the behavior of the crowds have a collective characteristic such as ‘an angry crowd’and ‘a peaceful crowd’ [22]. The scene could be determine when it reach the threshold below previous scene and considered both maximum similarity between the scene [23]. There are two categories involve in a crowd scene[24] : i) Structured crowded scene and ii) unstructured crowded scene. The algorithm based on the observation to track object in structured crowd scene and unstructured crowd scene is presented in [24, 25] . Figure 4 shows the sample image of several instances for structured and unstructured crowded scenes.

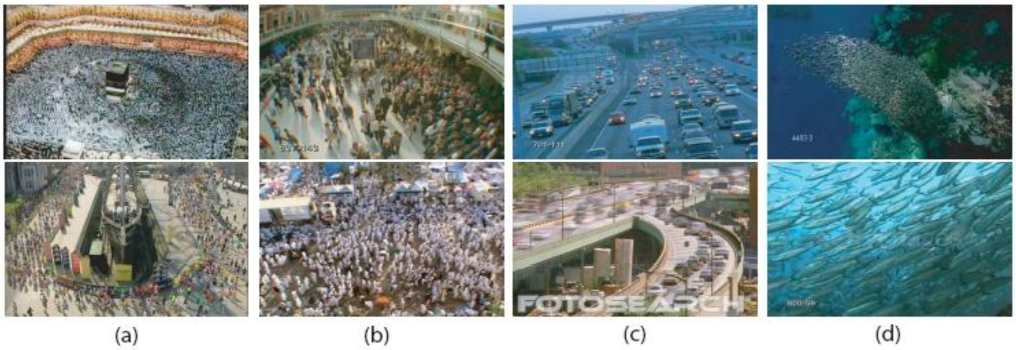

Figure 4 : Several instances of structured and unstructured crowded scenes. (a) Structured, (b) Unstructured, (c) Structured, and (d) Unstructured. [24]

In [26] studied about the motion and behavior of crowds instead describing a characteristic of a crowd, where the goal is to identify some patterns of the behavior in a crowd scene. People falling down (collapse), people fighting and crowd panicking can be assumes as the abnormal activities in a crowd. Generally for detecting abnormal behavior in a crowd, the process will be divided into two common task include crowd information instruction and abnormal behavior modeling [27]. The common process for analysis in video sequence of crowd information extraction composed the following main three steps include [7, 28-30] i) Pre-Processing, ii) Object Tracking, iii) Event/Behavior Recognition. The component of crowd analysis from the computer vision perspective are essentially describe by Zhan et al [6] at Table 4. In addition, Microscopic, Macroscopic and Mesoscopic or Hybrid are the three main category modeling approaches which are familiar in the crowd [17]. Table 5 shows the description of categories of crowd scene. The summarization for overall concepts of image processing in video surveillance and crowd analysis based on the understanding of behavior in crowded scene is presented in the framework at Figure 5.

Table 4 : Component Features of Crowd analysis in a computer.

Sensor typology and topology	Environmental conditions	Scene typology Individual Characters	Collective
Moving or Static Platform	Indoor/ outdoor	-	-
Number of camera	Level of clutter	Location/ velocity/ etc	Crowd density
Type of video sequence : color or gray scale, etc	Light condition etc	Appearance, etc	Average speed, etc

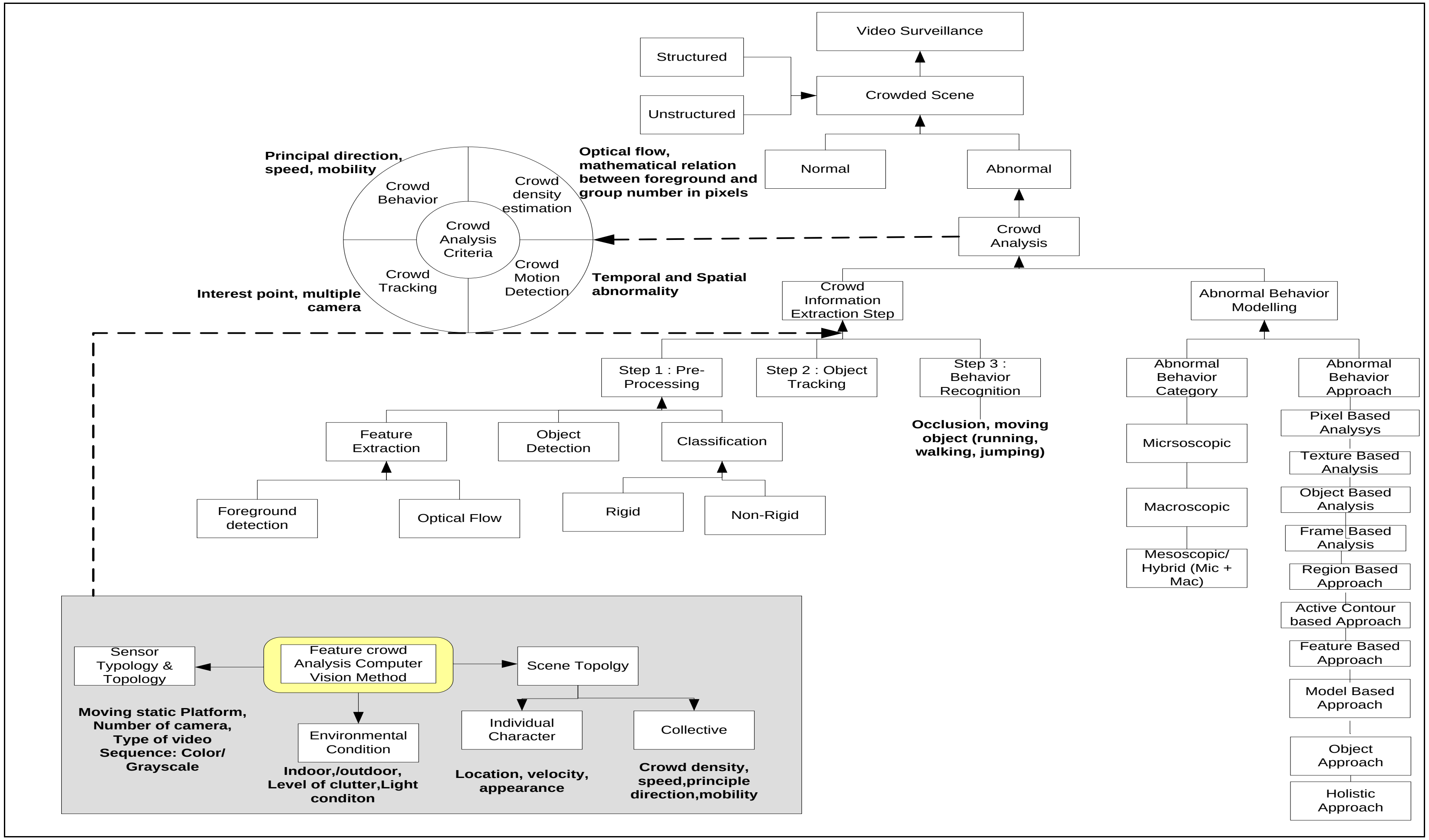

Figure 5: The framework for detection abnormal behavior crowded scene in video surveillance

Table 5: Terms and description in crowd analysis

Terms	Description
Crowd Density Estimation	To measure a crowd status. Find out the level of the crowd in a space or to detect abnormal changes of the crowd overtime
Crowd Motion Detection	To describe the characteristic of a crowd. Identify pattern of behavior in crowd
Crowd Tracking	To acquire the trajectories of movement. Determine whether abnormalities occur.
Crowd Behavior Recognition	To analyze the behavior of the crowd. Extract motion information and Model abnormal crowd
Structured Crowded Scene	Crowd moves coherently in common direction, motion direction does not very time, each spatial locations of the scene supports only one dominant crowd behavior over the time. *Example:* Marathon race, queues of people event, traffic on the road.
Unstructured Crowded Scene	Crowd motion is appeared random, different participants moving different direction at different times, each spatial location supports multi –modal, crowd behavior. *Example:* People walking on a zebra crossing in opposite directions, exhibitions, sporting event, railway stations, airport, motion biological cells.
Pre-Processing	*Responsibility* : Detect and classify *Category :* Rigid object or Non-Rigid Object *Analysis/ Features/ Approach :* Pixel Based Analysis, Texture Based Analysis, Region Based Analysis, Frame Based Analysis. *Example :* Feature extraction (foreground detection, optical flow), object detection, classification (color, edge, shape, head, body)
Object Tracking	*Responsibility :* Analyze target movement *Category:* Tracking individual objects and tracking the group of object. *Analysis/ Features/ Approach :* Region-based, active contour-based, feature-based, model-based tracking *Example :* Tracking speed and direction
Event/Behavior Recognition	*Responsibility:* Analyze pattern or behavior of the object. *Category :* Individual or crowd behavior recognition *Analysis/ Features/ Approach :* Object approach, Holistic approach *Example:* Occlusion, moving object (running, walking, jumping).
Microscopic	Defines the object movement and treats crowd behaviors as a result of a self organization process.
Macroscopic	Focus on goal-oriented crowds which determined a set of group-habits based on the goals and destination of the scene.
Mesoscopic / Hybrid	Inherit from Microscopic and Macroscopic

3 Overview of Abnormal Behavior in Crowded Scene

There are various ways to detect abnormal behavior such as density estimation, motion detection, tracking and behavior recognition.Table 8 Shows the survey paper based on human recognition in crowd to detect abnormal from 2000 till 2010.

Table 8: Publication on Abnormal behavior of human recognition and analysis from 2000 – 2010

Year	Author (s)	Density estimation	Motion detection	Tracking	Behavior recognition
Pulication 2000- 2010					
2000	Oliver et al			*	[31]
2002	Elgammal et al	*		[32]	
2002	Gong et al			*	[33]
2003	Cupillard et al			*	[20]
2004	Hua et al		[16]		
2004	Ma et al	[34]			
2004	Weiming et al	*A survey on visual surveillance of object motion and behaviors, 2004* [9]			
2005	Andrade et al		[35]	*	
2005	Lacks et al				[36]
2005	Vaswani et al		[37]		*
2005	Xinyu et al			*	[38]
2006	Andrade et al	[28]		*	
2006	Andrade et al		*		[29]
2006	Andrade et al				[30]
2006	Dimitrijevic et al		[39]		
2006	Kilambi et al	[40]	*	*	*
2006	Xiolin et al				[41]
2006	Xinyu et al	[42]			
2006	Yao-Te et al			[43]	
2007	Ali et al	[44]	*		
2007	Calderara et al		[45]	*	
2007	Cheriyadat		[46]		
2007	Duque			[47]	
2007	Jacques et al		[48]		
2007	Khansari et al			[49]	
2007	Ming-Yu et al		[50]		
2007	Peng et al			[51]	
2007	Yan et al				[52]
2007	Yufeng et al				[3]
2007	Zhi et al		[53]		
2008	Zhan et al	*Crowd Analysis Survey, 2008* [6]			
2008	Basharat et al		[54]		
2008	Blanc-Talon et al	*	*	*	[4]
2008	Bouttefroy et al	[55]			
2008	Cheriyadat et al	[56]			
2008	Ihaddadene et al		[57]	*	
2008	Li-Qun et al				[58]
2008	Zhi et al				[59]
2009	Antonakaki et al		*		[15]
2009	Garate et al			*	[7]
2009	Rodriguez et al			[24]	
2009	Kratz et al		[60]		
2009	Sharbini et al				[61]
2009	Fan et al		[62]		
2009	Mehran et al		[17]		
2009	Tian et al		[63]		
2009	Xiagang et al		[64]		
2010	Change Loy et al				[65]
2010	Djeraba et al		[66]		
2010	Husni et al	*	*	*	[2]
2010	Jacques Junior et al	*Crowd Analysis Survey*, 2010 [5]			
2010	Mahadevan et al				[67]
2010	Tziakos et al		[68]		
2010	Weina et al	[69]			

Papers are ordered first by the year of publication and second by the name of the author (s). Four columns allow the clarification of the contributions of the papers based on crowd analysis for abnormal behavior identification. The location of the reference number (in brackets) indicates the main topic of the work and an asterisk (*) indicates that the paper also describes work at an interesting level regarding this process.

3.1 Problem of detecting Abnormal in Crowded Scene

Although the analysis of abnormal behavior in crowd is a newly research topic in computer vision, some pioneering investigations of problem have already been made.

Year	Author	Issue (s)	Solution
2010	Weina et al [69]	Large numbers of constantly moving individuals. Blobs orientation is corrupted from vertical arms and legs extending out form the person. The likelihood functions does not discourage multiple overlapping shape at foreground pixels	Present mark process parameterized (MPP) model by extrinsic appearance (geometry) and intrinsic appearance (shape and posture).
2010	Tziakos et al [68]	Complex interaction between Multiobject and unrestricted scene cope with the non linearity, spatial locality of patterns and noise inherent such as high volume video data. Distinct sub-entities lead to different characteristic and crowd density	Present a non linear subspace learning detector
2010	Mahadevan et al[67]	Difficult to compare between representation of motion and appearance which are typically tailored in specific scene domain.	Present joint model (temporal and spatial) of appearance and dynamics, (Mixture of dynamic texture)
2010	Husni et al [2]	Several obstacles such as occlusion, illumination changes could influence detecting process in crowd scene. Difficult in analyzing crowd. computational cost increase processing time and cost expensive	Using double filter method to extract foreground image and media filter to reduce noise
2010	Djeraba et al [66]	Difficult to detect and track persons in crowd situations. Learning, adaptive and incremental processes are not solutions in dealing with abnormal events. Most of the methods do not take factors like density, direction and velocity.	Present three level features approach : low level, intermediate level and high level
2010	Change loy et al [65]	Anomalies are subtle and difficult to detect due to the complex temporal dynamics and correlations among multiple objects behavior. Different ways of deviations from the expected temporal dynamics lead to different types of anomalies. Anomaly difficult to detect if an object is viewed in isolation. No mechanism offers for discriminating different types of anomalies and reducing the effect noise and error from the observation space. .	Using Cascade of Dynamic Bayesian Networks (CasDBNs)
2009	Tian et al [63]	Impossible to interpret all the data manually for abnormal and emergency event in a crowd. It is not easy to describe for a most task in abnormal due to the fact that abnormality is often	Present crowd motion characteristic include crowd kinetic energy and motion directions based on optical flow technique.

		associated with change of motion such as gathering, scattering and chaos situation.	
2009	Mehran et al [17]	Difficulty in analyzing human activity in crowd. crowd motion demonstrate complex behaviors like line forming, laminar and turbulent flow, arching and clogging at exist, jams around obstacles and panic. Problems in tracking of high density crowd such as extensive clutter and dynamic occlusions. The limitation of the movement and actual motion would differ from desired direction and velocity.	Placed a grid of particles over the image and advected with the space time average of optical flow
2009	Fan et al [62]	Video scene hard to predefine normal behavior that requiring sophisticated work of labeling and training. Difficult to track individual object accurately due to the density of objects in a crowd scene.	Introduce new concept of contextual anomaly into crowd analysis which characterize the crowd motion by the patch based local motion representation.
2009	Kratz et al [60]	People and object within the scene move in highly irregular motion patterns in occlusions. The absolute number of subjects within the video makes analyzing each individual's actions a demanding task. The views recorded by surveillance cameras cover large areas and include hundreds of individuals. The motion analysis of trajectory-based approaches focuses on each subject individually, whereas the behavior of extremely crowded scenes depends on the motion of multiple subjects concurrently.	Present rich, non-uniform, localized motion pattern with 3D Gaussian distributions of spatio-temporal gradient.
2009	Garate et al [7]	High level of degeneration risk especially when a large number of people (crowd) are involved. Tracking individuals with occlusion may not be so scalable to crowds	Present HOG descriptors and recognize crowd events using pre-defined models.
2009	Antonakaki et al[15]	Many object's trajectory for behavior classification use the centroid of the target object or points in image which fail to determine the short term actions (man threateningly moves his hands). Facing problems such as dependency and occlusion when extract trajectories from one camera.	Present bottom up approach using short term behavior and trajectory of person
2008	Zhi et al [59]	Any change of regions shows the Instability in the flow.	Define a crowd energy based on markov random field using wavelet analysis of energy curves
2008	Ihaddadene [57]	Deal with problems such as motion detection and tracking. Required to select the appropriate threshold and regions of interest carefully.	Analyze the motion aspect such as tracking subject one by one which measures the crowd density, velocity and direction.
2008	Cheriyadat [56]	Difficulty in tracking invidual object accurately due to inter and intra object occlusion. High density crowd situation	Present the low level approach using optical flow

		pose such as parametric models, outer contours or blob centroid. Difficult to obtain reliable feature track in a crowd. Difficult to cluster the noise in motion trajectories.	
2008	Bouttefroy [55]	The challenges in high level process to detect abnormal because it require the integration of various technique such as feature selection, trajectory modeling, dimensionality reduction and density estimation.	Present Gaussian Mixture algorithm to update the probability distribution of objects behavior features.
2008	Blanc-Talon [4]	Large numbers of people gathering together in a crowd make it hard to detect. Humanoid detection does not perform the motion pattern under the high occlusion and in situations. Camera resolution not good enough to identify the feature. Suffer from difficulties such as inhomogeneous background, constantly changing crowd appearance and heavy computational costs.	Using a Scenario Recognition Engine (SRE) tool for fast modeling. Using a block matching across consecutives frames.
2008	Basharat [54]	Explicit estimation only captures the direct velocity for local application of a scene not in a global. Limited capability of detecting more complicated anomalies.	Present unsupervised learning that captures object motion and size at every pixel location. Integrate large transition time.
2007	Zhi [53]	Hardly find applications due to the limitation of computation in actual video surveillance systems.	Present modeling and processing in the real time surveillance with wavelet analysis of energy curve.
2007	Yufeng [3]	Difficulty in recognize human actions. Individual local features are limited for understanding the global characteristics in a crowd scene. Difficult to define abnormal behavior with the motion sequence because human action static with the same pose in a crowd. Contour feature cannot always be detected in crowd.	Present action recognition features using multi SVM method to learn and recognize human actions from motion information
2007	Yan et al [52]	Difficult in segmenting the actor from the background owing to distraction motion from others object in a crowd scene.	Match volumetric representation that against oversegmented spatio temporal video volumes, enhance shape-based using flow, separately match by parts (space or time)
2007	Peng et al [51]	Traditional SMC unable to model the spatial dependency of state that presenting the interactive events. Detect anomalies in individual and interactive event sequence. States are hidden, noisy observation and transformation either linear or non linear.	Present MRF with SMC to extend the ability of tracking both individual and interactive events. Present pixel-wise event to construct feature images, transform blob level features into subspace.
2007	Ming-Yu et al [50]	Difficult to maintain plausible background model for background subtraction. Human operator work long hours on watching online surveillance for monitoring. Multiple cameras generate high volumes video signals	Incorporate structure information of moving blob with stereo vision which is analyzing the motion of each pixel to recover only motion in background pixels. Present object blob detection and object shape detection with the

		make it difficult for human operator to handle. Error and incorrectly align the background pixels generate by feature localization, motion model assumption, motion parameter estimation and lens distortion.	calculation of optical flow..
2007	Khansari et al[49]	Noise effect gives an impact to the image and video representation signal. Similar object (head) hardly changes the color histogram.	Present the analysis of adaption of a feature vector generation and block matching algorithm in the Undecimated Wavelet Packet Transform (UWPT) domain which can manage noisy environment of object detection in crowd scene
2007	Jacques et al [48]	Large numbers of video cameras are monitor by a single user. Unworkable to visualize simultaneously behavior with the large amount of data.	Present behavior analysis called Dynamic Oriented Graph (DOG) that could detect, predict and identify abnormal.
2007	Cheriyadat et al[46]	Difficult to track individual object in a crowd scene accurately due to inter and intra object occlusion.	Present a clustering into dominant motion using distance measure for feature trajectories based on subsequences.
2007	Ali et al [44]	Lack of information direction and pose when involve in high density scene such as gathering events. Inability to handle crowd scene.	Propose Langrangian Particle Dynamic framework for segmentation of high density crowd flows and detection of flow instabilities.
2006	Yao-Te et al [43]	The overlapping of different object in the optical flow during occlusion probability unreliable and cannot be used to predict moving objects	Propose each pixel to different human object based by calculating the distance between object and compute the probability and color model.
2006	Xinyu et al [42]	Large amount of instances of abnormal crowd gathering in public places. Object with the same size will be smaller in the image when it is far from the camera so it hard to detect and recognize the image clearly.	Presents multi resolution images cell to obtain the texture feature by intoducing Harris Laplacian space as the searching technique. Enable to detect some abnormal density distribution such as overcrowdedness and overemptiness in local area.
2006	Kimambi et al [40]	Difficult in monitoring due to the number or density of people in crowd scene. Head is not reliable when occupy only a few pixels and require reasonably close view of the scene.	Using a Kalman filtering technique to track the group as the individual and provide various size of moving in unconstrained fashion in crowd scene.
2006	Andrade et al [30]	Large variation in densities and motion s in real crowd. Hardly to specify particular label for behavior analysis in crowd.	Characterize the crowd behavior using the crowd optical flow by fitting the hidden markov model and spectral clustering as the unsupervised feature extraction to find the optimal number to represent motion pattern.
2006	Andrade et al [29]	Difficult to predict and not easy to translate semantically crowd behavior. Difficult to track individuals in the crowd.	
2005	Andrade et al [35]	Large scale and huge amount of data make difficult in monitoring. Occluded situations tracking fails due to the difficulty in resolving individual in a crowd scene.	
2002	Gong et al [33]	Difficulty in understanding behaviors lies with the ability to map automatically measure semantically in visual representation (cannot measure	Introduce a learning structure using CONDENSATION which apply the pixel wise energy histories for extracting high level semantic human

		directly). Visual is change over time. Involves multiple interactive human actions in a crowd.	behavior pattern without participating the segmentation of object centred trajectories.

3 Taxonomy and Pattern Abnormal Behavior Detection

As mention in section II, there are three processing steps to do crowd analysis, which consists of pre-processing, tracking and event/ behavior recognition. The pattern for abnormal crowd analysis will be presented in a taxonomy based on the survey paper at Figure 6.

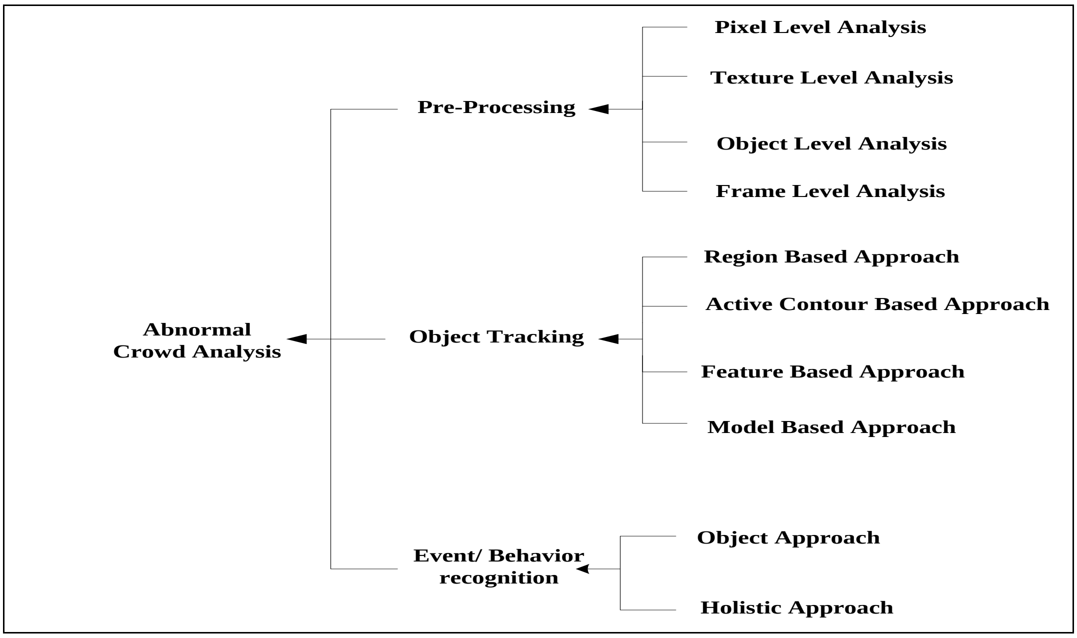

Figure 6: Taxonomy and Pattern Abnormal Behavior Detection

4.1 Pre-Processing

One of the important steps in pre-processing is feature extraction. Feature extraction always deal with the crowd density which is very useful in source information. Due to the strength of the feature extraction in detection, most of the researchers are intended to analyze and learn the pattern of abnormal in crowd scene.

4.1.1 Pixel Level Analysis

Pixel level analysis is obtained through edge detection or background/foreground subtraction. Mostly focus on a low level features where extract the information based on density estimation rather than counting.

Andrade[28] adapt mixture of Gaussian algorithm for the change detection where applied the optical flow calculation to provide a smooth and useful at motion boundaries. Noise can be reducing by combining optical flow and foreground mask. They used Expectation Maximization (EM) algorithm by analyzing pixel based to determine the variables and to update the equation of the probability distribution. According to Ma et al [34], the crucial performance in a surveillance consist of foreground segmentation. Learning function of foreground pixel is applied with geometric correction (GC) to measure the various distances into same scale. Affine transform and integrate GC in a pixel are used to perform a pixel counting for fast implementation of scaling. Crowd density histogram is used to normalize the record data and threshold over the long periods. Boutterfroy [55] update the feature probability distribution in local model to allow smooth transition and provide fast discrimination between normal and abnormal behavior. Probability density estimation (pdf) is adapt to approximate the behavioral component in a local function. Gyu-Jin and colleagues [70] measuring the number of edge pixel in a big city to prevent a crime. Optical flow vector and edge pixel are presented to classify the crowd density information. Intensity constancy is used at each image pixel to remain constant with time at any point on any object. Whilst edge detection is used to give better edge of image in the background without being affected [71]. In Xiaogang et al [64] works, simple "atomic " activities and interaction in a low level features is proposed for unsupervised learning framework. Both activities and interaction are clustered into different class (eg : moving pixel- atomic; short video clips - interaction). The solution such as transparent, clean and probabilistic are formulated for solving the surveillance issues. On the semantic visual behavior in a crowd, Gong et al [33] explicit motion group by modeling the dynamic pixels using adaptive Gaussian Mixture based on color distribution. Ignoring the segmentation process for illustrate the abnormal. Gaussian Mixtures model is used to examine the change (short term and long term) spectrum, Mahalanobis simply classify the threshold binary and Bayes rules for formulate the probability of pixel value in a foreground component.

4.1.2 Texture Level Analysis

Similar like pixel level analysis, texture level analysis also use to estimate the number of people rather than identifying individual in a scene. The analysis of image patches is required for modeling and mostly focus on high level features. Texture level analysis is used by Xinyu et al [42]. They analyzing the texture based on the contour for human blob. They learn different scale of group using Gauss Lapcian kernel function. The supervised PCA is performing to emphasize and make the features resembling data easily. Elgammal et al [32] mention that it is necessary to represent higher level understanding in a certain low level of computer vision tasks to achieved efficiently detection of interaction between people. Weighting coefficient and kernel density estimation are used at centre data point to estimate having store at complete data whilst average image in the scene. However, the suitable scale should be chosen correctly when dealing with the kernel density estimation technique.Another author that learning the abnormal detection based in texture is Kilambi et al [40] by learning the shape model to estimate the accurate people in the scene. The measurement is based on shape and heuristic. Heuristic based, is measure by scene coordinate assuming that object (people) is moving in a ground plane. Advantages using heuristic based include robust false detection, remove shadows and eliminate variation of distance area.

4.1.3 Object Level Analysis

Object level analysis is identifying individual object in a scene. More accurate result will be produced when compared to pixel and texture analysis. In Khansari et al [49] works, to find the direction and speed of the object motion, inter frame texture analysis is adapted for the searching window. To perform the best matching region, frame is successfully generated with feature vector in a search window.

4.1.4 Frame Level Analysis

Frame level analysis, model behaviors of the full scene within the field of view of a camera [68]. Related to Oliver et al [31] work, robustly 2D blob features is presented. Eigenspace describe the appearance in a covariance data whilst principal component analysis used to reduce the dimensionality space. However, eigenspace could not distribute the moving object efficiently in the background. Therefore, to get more accurately detection of abnormal to characterize the shape of each person, the portions of containing image moving present in the scene is well managed using frame by frame examination.

Table 9 summarizes the differences of identification accuracy on different abnormal behavior in of human crowd scene. Thus, we can state that different abnormal behavior leads to different approaches in order to achieve competent detection.

Table 9: Feature Extraction, Type of pattern and Methods with multiple behavior patterns.

Authors + References	Feature + detection method	Level Analysis	Behavior pattern	Summary	Detection result
Ma et al [34]	Feature : Object detection Method : Geometric correction + time adaptive criterion	Pixel	Walking, standing	Better fitting technique (non-linear) for high crowd density estimation	Covering 95 % under the crowd area.
Oliver et al [31]	Feature : Motion Vector Method : Kalman Filter-generated spatial PDF + Gaussian color PDF + Mahalanobis distance	Frame	Meet and continue together (1), meet and split (2), follow (3)	Accurate classify real behavior with no additional tuning or training	Accuracy : 1 = 100 % 2 = 100 % 3 = 93.7%
Gong et al [33]	Feature : Object + Motion : Method : Adaptive Gaussian Mixture + EM algorithm	Pixel , Frame	walking leaving	Semantically discriminate motion without segmentation and grouping	Accuracy provide less frames error, 13 % while the other is more
Andrade et al[28]	Feature : Motion Vector Method : Adaptive Mixture Gaussian + EM Algorithm + Gaussian spatio-temporal filter	Frame	People push, person falling	Provide smooth optical flow at the motion boundaries and reducing observation noise	Accuracy present 80 % likelihood for the person falling
Kilambi et al[40]	Feature : Object + Motion Method : Kalman Filtering	Texture	Move together with a fix gap, people touch each other	Invariant view-point	Accuracy less than 75 % ::Shape based estimator is more accurate than heuristic method
Xinyu et al [38]	Feature : Object + motion Method :PCA + SVM classifier + DFT	Texture	Running (1), bending down movement while most are walking or standing (2), person carrying long bar (3)	The velocity and noise removed by threshold.	Abnormal: 1= 82% 2=86% 3 = 87% Normal: 97%
Bouttefroy et al [55]	Feature : Motion Vector Method :GMM + Mahalanobis distances	Pixel	Pedestrian walking on the highway	Reduce the computational load	Accuracy Detection rate 95%
Calderara et al [45]	Feature : Von Mises Distribution + K medoid clustering algorithm + EM algorithm + Bhattacharyya distance	Frame	Different people moving	Robust segmentation errors and non-idealities	Abnormal rate : 100% Normal rate : 94.4 %
Djeraba et al [66]	Feature : Object + Motion Method : optical flow + blob + entropy	Object	Collapse	Efficient target on a motion ratio	Recall = 0.928 Precision = 100% No false alarm
Peng et al [51]	Feature : appearance Method : Markov Random Field (MRF) +	Pixel	Walking, Browsing, Collapse, Leaving objects, Meeting	Available to estimate posterior probability	Detecting rate = 100%, False alarm = 10%

	Sequential Monte Carlo (SMC) + Event Sequence (ES) + Particle advection		and Fighting		
Mahadevan et al [67]	Feature : appearance Method : Mixture dynamic texture +GMM +PCA	Pixel	Walking across a walkways, walking across the grass surround	Performance is more pronounced in the anomaly localization task	Accuracy: At least 40% of the truly anomalous detected.

4.2 Object Tracking

The next steps after extracting the features from the image sequence is object tracking. Object tracking in a crowd attempt to minimizing the constraint such as occlusion, color intensity, illumination condition, appearance and etc. Past few years, multiple human objects tracking approach has been applied by researcher for recognize and detecting the behavior in a crowd, which is consist of identifying the position of each person in the same video sequence. There is various effective parameters ways. For example color, trajectory, body contour (head, hand, foot), and etc. Color distribution is commonly used in tracking to differentiate the object in a crowd [43] [49] [72]. Note that, it is easier way to track and understand the behavior of the people in crowd rather that individually as long as their moving in the same direction. By assigning the object distance , the occlusion in a crowd could easily track independently, as in [43]. However, if the pixel could not classify in the object, it is difficult to find the reliable central of the occlusion as long as the presence probability is updated for every pixel in the frame correctly.

4.2.1 Region Based Approach

Region based approach is a robust computer vision in unconstrained crowd scene [72]. Weighted Maximum Cardinality Matching scheme with disparity estimation technique are presented by Kellly et al[72] to evaluate both environment condition either indoor and outdoor (eg : varying cloud clover, shadows, reflections on windows and moving background). The detection is performed based on 3D clustering whereby variant placement and orientation of different camera is presented. In post-processing, the authors created a region in a foreground and background segmentation.Crowd motion analysis to detect abnormal behavior in crowd scene through the region approach is presented by Ihaddadene et al [57]. Point of interest (POI) is set to estimate the sudden changes of abnormal motion. The information such as density, direction and velocity is extracted using optical flow technique.

4.2.2 Active Contour Based Approach

Khansari et al [49] typically has been used a color histogram as the active contour based approach to model the target partial occlusion and to extent some noise. But, the weaknesses by using this technique is hardly change the color histogram when impair with similar object such as head in a crowd. Beleznai et al [73] obtain maximum of posterior (MAP) by presenting Bayesian detection based on shape and cues. The contribution of their works include image contour intergration and object parts generations in occlusion. Figure 7 shows the outline of the proposed human detection method in [73].

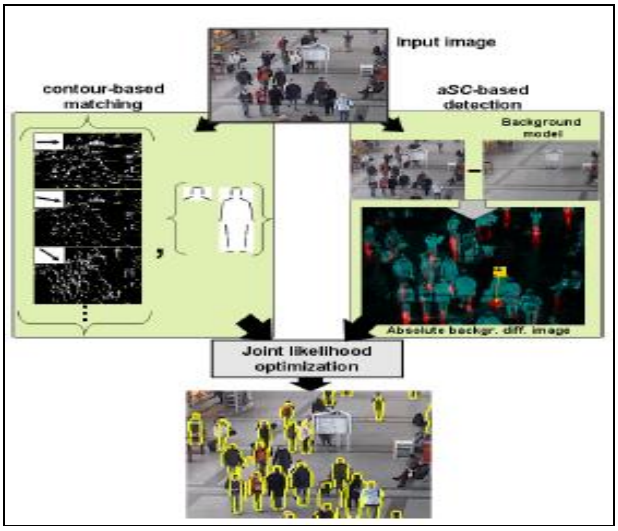

Figure 7 : Outline of the proposed human detection method by Beleznai [73]

4.2.3 Feature Based Approach

Feature based approach is presented in feature image by describing the blob level feature. The examples are size, shape, elongatedness, luminance histogram and displacement histogram [51]. Peng et al [51] introduces a pixel wise to detect anomalies in individual events sequence by constructing feature images. Each feature image is transform from original blob level features into probabilistic appearance manifolds for each class.

Bayesian framework, design probability based on image cues, and corporate color based model during tracking with mean shift. Yao-Te et al [43]introduces model based object to estimate the positions corresponding to optical segmentation, which allow multiple object to be detected and track in crowded scene. To differentiate each object, color model of two region of body is presented called torso and bottom. Figure 8 shows the sample images to detect and track human object based on torso and bottom.

Figure 8 : Sample image based on Torso and bottom

Recently, many innovative methods and approaches have been developed for tracking abnormal behavior using region based approach, model based approach, feature based approach and active contour based approach. However, each of the method proposed has pros and cons. Table 10 summarizes the comparison on advantages and disadvantages of detection methods.

Table 10: Features and method for tracking abnormal in a crowd

Author+ References	Features + tracking method	Analysis type	Advantage	Disadvantage
Yao-Te et [43]	Gaussian Mixture Model (GMM) + Bayesian Classification + HIS + EM algorithm	Model based	Reduce illumination changes	Need to update presence map for every pixel
Khansari et al [49]	Chi-square + Bhattacharyya + Undecimated Wavelet Packet Transform (UWVT) + EM algorithm + biorthogonal wavelet bases	Active contour based	Noise has degraded without having any effect in our method	Color histogram cannot handle partial occlusion in the sequence
Peng et al [51]	Markov Random Field (MRF) + Sequential Monte Carlo (SMC) + Event Sequence (ES) +	Feature based	Abnormal is detected by too high ELL value	Traditional SMC unable to model spatial dependence state
Kelly et al [72]	Maximun Weighted Maximum Cardinality Matching + color histogram	Region based	Minimize shadows and background illumination changes	Not interested in detection the correct number of people corresponding to a person
Rodriguez et al [24]	Correlated Topic Model (CTM) + Scene Codebook + Kalman tracker + EM algorithm	Model Based	Able to capture different behavior modalities at specific locations in the scene.	Not unique to rely on disparity, foreground segmentation or edge gradient.

Khan et al [74]	SIFT feature matches + RANSAC algorithm	Region based	Prune out false detection and increase robustness of localization	Do not handle split and merge otherwise require an explicit split merge analysis.
Ihaddadene et al [57]	Region of interest (ROI) + Kanade Lucas Tomasi +entropy	Region based	Remove a static and noise features.	Necessary to select appropriate threshold and region carefully

4.3 Event/Behavior Recognition

Another important process in a crowd analysis is event/behavior recognition. It can be characterized by regular motion patterns such as direction, speed, etc [7].Variety approaches were proposed to estimate the behavior in a crowded scene. Behavior of human recognition also has been studied and documented by sociologist and psychologist [1]. In the early work, crowd behavior analysis has been attempted in research topic of the computer vision especially in simulation [26] [75-77] and graphic field. Monitoring and modeling the crowd is not so much to analyze normal crowd behavior, but to detect something different behavior from it. These are referred to as anomalous or abnormal.

Related work, Reynold [75] was the early person who model the motion of object within the environment called boids of flocks which is the most basic pertaining for the human crowd behavior algorithm based on crowd simulation. Flocking model decomposed complex behavior into three simple steering behaviors which describe how an individual boids manoeuvres based on position and velocities its nearby flock mates. However, this flocking is only sufficient for the appearance of human crowds in film but not in the realistic behavior because there is no ability to make a decision such mental model, emotion and motivation in a complex behavior [78].

In 2008, Thalmann and Musse [26] presented a simple hierarchical and empirical model for real-time simulation of virtual crowd based on the observation. Thus, the model is based on studying the motion of real group of people or otherwise they could discuss some aspect such as crowd characteristic and behavior pattern of real people in virtual crowd. However, to generate the motion of virtual agents based on real-life scenarios is quite challenging problem in a crowd simulation. Furthermore, it is necessary to achieve some actual trajectories from real scenarios in order to obtain the time consuming task that requires large amounts of human interaction. Vigueras et al [76] proposed a scalable architectures which requires partitioning methods in order to handle the simulation of large crowds in the field of soft computing. They analyze existing distributed resource for solving the partitioning problem. Bruno et al [77] modeling crowd dynamic framework where the structure of the crowd deployed in most numerical solution techniques which is applied in the mathematical modeling field.

4.3.1 Object Based Approach

Object Based Approach, a crowd is analyzes by treating a collection of individual to estimate the velocities, direction and abnormal motion. The complexity occur when the occlusion exist that maybe could be affected the process of analyzing such as detection of object, tracking trajectories and recognizing activities in a dense crowd [17]. Mehran et al [17] compute the concept of social force model to track object in a crowd and to estimate the parameter. Thus, interacting particles is used in estimating process in order to observe the dense of human movement in crowd. Weina Ge et al [19]. Jacques et al [48] use a position of each individual in parameter to obtain and characterize (voluntary or involuntary) the formation in a group and Voronoi diagram was used to understand people motion. Two approaches were proposed include feature correlation and binary function. Feature correlation was use to find the approximate position of the center of head while binary function is defined to represent distance between agents. Cheriyadat et al [56] proposing the clustering partial feature trajectories in a low level feature to identify the dominant object motion in a dense crowd. The framework automatically defines the trajectory as a set of point to represent the length of the track depending on the duration.

4.3.2 Holistic Based Approach

Holistic Based Approach, a crowd is analyzes by treating a single entity to estimate the velocities, direction and abnormal motion. The analysis covers medium to high density scene in global entity [17]. Weina Ge et al[19] focus on tracking individual through the crowd by forming the mid level analysis at the ganualarity called symmetric hausdorss distance (SHD) set. SHD defined paiwise proximity and velocity to validate the quantitative and qualitative of real world videos of pedestrian scenes. Mehran et al [17] integrates holistic approach with a particle advection method. They underlie the flow field with social force to extract interaction to determine the change interaction of time of behavior of the crowd for mapping to the image frame.

5 The Methodology of Abnormal behavior detection in crowded scene

Abnormal behavior analysis in a crowded scene is one of the most crucial tasks. Abnormal are themselves defined in a somewhat subjective, sometimes according to what algorithms can detect [67]. There are numerous method in the literature to cope with abnormal detection in a crowd scene such as Bayesian

Approach [31, 33, 39], Support Vector Machine (SVM) [3, 42, 66] , Hidden Markov Model (HMM) [28-30, 35, 60], Markov Random Field (MRF) [67, 79], Gaussian Mixture Model (GMM) [43, 55, 63, 80-86], Social Force Model[17] and etc. Table 9 will summarize the function of each methodologies based on the survey paper

Table 9 represents various methodologies with function to detect abnormal behavior in crowded scene based on the survey paper from 2000 till 2010.

Method	Ref.	Function
Hidden Markov Model (HMM)	[28-30, 35, 37, 57, 60, 87-90]	• Capture and learns variations in optical flow pattern. [28-30] [35] • Allowing discrimination of abnormal behavior[28] • Allowing classification of normal and abnormal behavior [35]. • To encode visual context to perform inference[35] • To minimize false-positive error while maximizing detection rate [87] • To smooth sequences of actions [88] • Able to extract two kinds of data information: static and dynamic [89] • To cope with the variable number of motion samples [30] • Represent temporal dynamics to achieve varying sequence length and position of the anomalies within a sequence [90]
Correlated Topic Model (CTM)	[24]	• To capture different overlapping and non-overlapping crowd behaviors in the scene [24] • To handle multi-modality of crowd behavior [24] • Enables to bypass the object detection within class of crowded scenes , direct processing on low level flow vectors [24]
Bayesian Network	[31, 33, 38, 39] [64, 88, 91]	• Classifying, modeling and recognizing human behaviors interaction between people [31]. • To separate model and recognize slow change such as illumination cycles under a less computational [33] • Distinguish and predict the human motion [39]
Gaussian Mixture Model (GMM)	[43, 55, 63, 80-86]	• Model the color of torso (or clothes) and bottom (or pants) of a human object [43]. • Update the parameters to fit the probability density [55] [84] • Allow smooth transition for neighboring locations [55]. • Generate mask from the foreground [63] [54] • Adapts to slow background changes such as illumination variations [82] • Extract human silhouettes to get texture information [85] • Learn the characteristics of each motion pattern [86]
Markov Random Field (MRF)	[67, 79, 82] [80]	• Reduce scattered false detections and smoothing region boundaries [67, 82] • Extract blob from motion pattern [80]
Sequential Monte Carlo (SMC)	[51]	• Provide finite dimensional approximate to the posterior probability [51]. • Flexible, easy to implement and applicable in setting [51]
Neural Network : Support Vector Machine (SVM) Feed Forward Neural network (FFNN) Self Organizing	 [3, 42, 66, 92] [38] [93] [1]	 • Strong theory-interpretation and better generalization [38] • Tunable parameters and the use of structural risk minimization [42]. • Extract and identify feature area either the contour is a head or not [66] • Identify anomalous trajectory [92] • Learn and model paradigm to test the motion pattern from the trajectory based abnormality. • Used in mapping multidimensional data onto a low-dimensional map [1]

Map (SOM)		• Capture the two major components of the crowd dynamics: occurrence and orientation [1]
PSO	[94]	• Matching the search target object frame • Search the global based on three weight factors: inertia velocity, cognitive effect, social effect to find the best position in neighbors.
BP	[95]	• Training and classifying several grades
Social Force Model	[17]	Treat and localize abnormal moving particles individual in a crowd [17]
Dynamic Oriented Graph	[47]	• Identify and predict object behaviors [47] • Arrange the nodes to define the distributions of object properties each time segmentation [47]

6 Conclusion

Video surveillance and crowd analysis are the most important concept for understanding the behavior especially in analyzing to detect abnormal behavior in crowd. We have to cope various obstacles to tackle the problem in order to make the detecting abnormal in crowd successfully. The obstacles maybe come from the different characteristic (involving different pose, position, velocity and density), changes of motion over time in a real video sequence, the occlusion surrounding people in crowd, illumination changes (transiton from day to night, shadow of background images and non static background like leaves blown by the wind), and multiple input channel with the amount of numbe of camera where put many sides. However, with the variant analysis apply in a crowd analysis, these obstacles could be solving. Three processing involves in crowd analysis including pre-processing, object tracking and event/behavior recognition. For pre-processing, four types of analysis are commonly used such as pixel level analysis, texture level analysis, object level analysis and frame level analysis. For object tracking process, four types of approach are commonly used include region based approach, active contour based approach, feature based approach and model based approach. And for the event/ behavior recognition process, two approach are commonly used include object approach and holistic approach. Different results of false alarms rate are determined in this studies.

Further research currently in progress includes exploring the classification phase in detecting abnormal behavior of poultry in crowd scene. However, our hope that, these studies on the state of art would be useful to researchers the related field and will serve as a good introduction related field undertaken.

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